'A Study on Volatility and Leverage Effect in Bunker Markets'

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Abstract

This research primarily focuses on analyzing the volatility and to study the leverage effect in the bunker prices specifically in IFO 380 AND IFO 180. To achieve this objective the research has used econometric model to study volatility known as ‘Exponential General Autoregressive Conditional Hetroskedasticity (E-GARCH). The time period chosen to analyze this data was from January 2000 to October 2015. The second objective in the research deals with investigating the impact or causal relationship of IFO 380 bunker grade on bunker grade 180 and vice-versa. In order to achieve this Bivariate analysis was done.

The motivation behind this research was to study the leverage effect present in E-GARCH and based on results analyze where to risk mitigating strategies (hedging strategies). Also this research included aspects (problems and its corrections) of serial correlation seen through LM tests and heteroskedastic problems in the Bunker price data which affects the results. The literature showed different research which dealt with volatility and GARCH models but with tabulation of all the literature a common research gap was found that there are limited studies on Bunker prices (especially dealing with IFO 380 and IFO 180) using E-GARCH and Bivariate analysis.

The results were obtained through E-Views software. The software exhibited the model to be highly significant at 1% level of significance. The IFO 380 and IFO 180 were observed to have short and long run shocks and additionally a positive leverage effect was seen in IFO 180. Also a strong and apositive impacts were observed between IFO 380 and IFO 180 prices. Based on these results and studying the volatility the recommendations were presented.

Key Words: Bivariate Analysis, E-GARCH, leverage effect, hedging strategies, IFO 380, IFO 180, E-Views, LM tests and Hetroskedasticity tests.

Chapter 1

Introduction

‘Bunkers’ is the generic name for the fuel used by ships. It is obtained in the refining process of crude oil. The original usage came from the use of coal as a fuel for the boilers on the first team ships. The coal was stored on board compartments either side of the boiler room and these compartments were called Coal Bunkers. Bunkering is a term used in maritime world is used to describe the supplying the fuel to the marine vessels or ships.

1.1 **Size of the Bunker market:**

The world market for the residual fuel is about 200 million tons per year and the demand of the residual fuel is expected to increase by 90% in the developing countries(Bunker Consumption Outlook, 2016). However the total bunker market is forecasted to reach upto 460 million tons by 2020 (Transparency Market Research, 2015). The largest bunkering hubs are in Singapore were over 40 million tons of bunker fuels a year are now delivered, Fujairah in the Middle East about 24 million tons per year are delivered while in Amsterdam/Rotterdam/Antwerp (ARA) where almost 11 million tons per year are delivered (Ship & Bunker, 2016). The residual oil market has grown in line with the growth of the world scale. According to (Draffin, 2008) bunker prices account for 50%-60% of the total voyage cost at the on-going prices. Bunkers have always been an important part of the ship operations and bunkering is a vital part of an owner’s day to day operation. Bunker prices are just as much market-driven as freight rates, but the market price of bunkers is far from the only cost involved.

1.2 **Bunker Grades:**

Bunkers can be segregated mainly into three types: Intermediate Fuel Oil (IFO), HFO (Heavy Fuel Oil) and MDO (Marine Diesel Oil).The research (Stefanakos and Schinas, 2014) mentions that there are various categories and classifications of marine fuels. The classification of the International Standard Organization (ISO) protocol ISO 8217(E), is under two amendments for the year 2005 and 2010, while the categories are on the basis of ‘distillates’ and ‘residuals’. The paper also mentions details about two broad categories of marine fuels namely, Distillate’ fuel MGO is Marine Gas Oil which is known for distillate only and can also be used as home heating oil. While, MDO is Marine Diesel Oil known for the blend of heavy gas oil that may contain very small amounts of black refinery feed stocks, but has a low viscosity up to 12cSt so it does not need to be heated for use in internal combustion engines. Rest three marine fuels comes under residual fuels named as HFO (Heavy Fuel Oil): High-viscosity residual oil, MFO (Marine Fuel Oil): Same as HFO and IFO (Intermediate Fuel Oil): A blend of gas oil and heavy fuel oil, with less gas oil than marine diesel oil. Distillates’ or Residual fuel oil stocks are mixed

with blending components or cutter stocks to achieve internationally accepted product specifications. IFO has two major divisions namely IFO 180 Centistokes and IFO 380 Centistokes. This 180 and 380 are differentiated on the basis of their viscosities. For each individual market, differences in refining capacity infrastructure and storage capacity, sales volume & competitive bunker price for physical bunkering activities exist.
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1.3 **Bunker Prices:**

Experts from the maritime industry have commented that some factors which determine the bunker prices and help in the volatility analysis are as under:

1) Raw Material Prices (Bunker prices are derived from the crude prices)

2) Availability of bunker at the different places, eg. prices at the bunkering hubs like Singapore Fujairah Rotterdam & Houston are different. These differences are mainly because of the number of suppliers available in that location.

3) Geopolitical Factors- There are several geopolitical reasons associated to the bunker price decisions like Sanctions on Iran leading to no supply of Bunker, Fires at the Canadian Oil Sands leading to stoppage of production and Nigerian unrest by militants preventing oil movement.

4) Congestion at the port while bunkering- When bunker barges are waiting to fill in the bunkers and not getting time for loading, hike up in bunker costs are observed.

5) Seasonal Factors: During monsoon season , considering a case of the port of Cochin, where the bunker suppliers take place at anchorage which is about 9-10 miles away from the port. In monsoon season, these require suitable class approved barges (higher prices at these are strong barges) for the effective supply at the anchorage. This can be considered as additional cost along with the bunker cost. So the overall cost of the bunker prices increases. This fact is also supported by the analysis presented by ship bunker which shows that, with the relative cost of crude oil going down, the bunkers too are getting cheaper(Pedrielli, Lee and Ng, 2015). The bunker oil is known to be indexed according to the crude oil and hence the two are positively correlated according to Peter Sand from BIMCO.

Summing up the factors the bunker prices majorly depend upon supply and demand factors. The demand for bunkers emerges from the rising shipping demand. Consequently, any factors affecting the shipping demand such as the world’s economy, international seaborne trade, seasonality factor, political disturbance, and transport costs will affect the demand for the bunker. In the supply-side dynamics, the factors directly affecting bunker price are examined such as the world oil price, the local demand, the refining capacity, the degree of competition among suppliers and the bunkering methods.

The outlook for oil prices is very crucial for the bunker market considering the strong relationship between the two and the main cause for volatility. From the operator’s point of view, low bunker prices are a boon but they are causing deep concerns in the oil-producing economies. Figure no 1 shows the historical bunker prices (Singapore IFO-180 and IFO 380) moving in line with crude oil price showing a strong correlation. These Brent, WTI and Dubai's average prices are mentioned in annexure 7.2

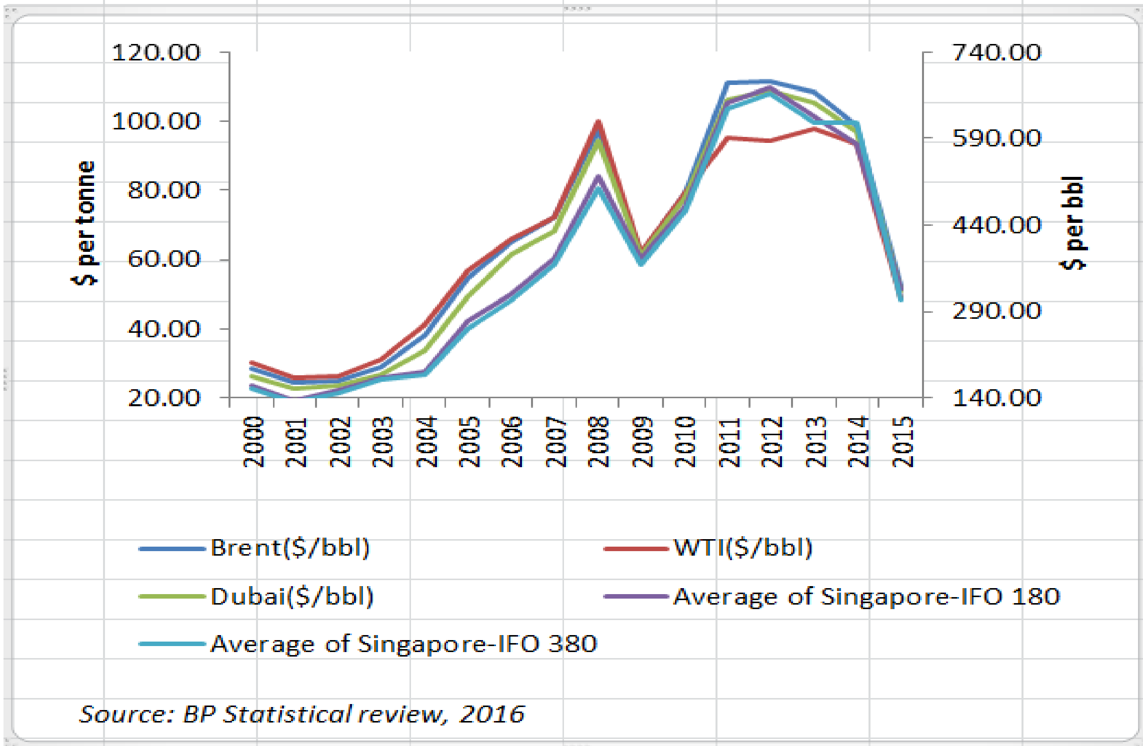

Figure 1: Historical Bunker Prices for Singapore IFO- 180 cSt

Apart from these, there are extensive literature studies commenting on the fluctuations in the bunker prices and also risks associated with it. The research (Stefanakos and Schinas, 2014) mentions that the maritime industry is associated with high risks for example the ship owners, operators, charterers and all other related parties are exposed to the fluctuation of vessel prices risks, interest rates and currencies and freight rates and bunker (marine fuel oil) prices. Hence risk mitigation portfolios are made to be risk- averse as these fluctuations impacted on the financial viability of the cash inflows.

Due to these fluctuations, volatility studies are done and respective hedging strategies against bunker price fluctuation are taken care. The fluctuations and forecasting studies are done and respective hedging strategies against bunker price fluctuation are taken care. Forecasting studies require locks in amount of money involved in shipping, and efficient forecasting of the bunker prices would help the shipping ventures to be successful and incur fewer risks.

1.4 Leverage Effects

Volatility and Leverage effects play an important role in the bunker market. Leverage is a financial jargon which means to use borrowed money to increase in the returns of an investment. If a company is financing firms’ assets through debt more than by equity, is said to be highly leverage firm.
The paper (Chevallier and Ielpo, 2014) measures leverage effects in commodity markets. The paper highlights that leverage effects define major three things; Volatility asymmetry, Standard Conditional Returns and Conditional Skewness. It discusses about the persistence of positive and negative shocks. Also, the negative returns include volatility spillover effects and these effects are useful in diversification of risks thereby mitigating the risks.

1.5 **Bunker Forecasting**

The study (Platts, 2017) commented that the 2016 was a rough year in the shipping industry and companies on the verge of closing, but 2017 is unlikely to see much dramatic fluctuations. Experts from Marine & Energy Consulting (MECL) as well as chairman of the International Bunker Industry Association (IBIA) have quoted that “demand for bunkers will be steady or slightly less volatile compared to last year. Moreover, in the interview with (Torres, 2016) Global Head of BP Marine Fuels, he mentioned that the global demand for marine fuels can grow as much as 25% to touch 300 million mt next year and thus affecting the bunker prices in the positive way. He also mentioned that, the port of Singapore and Panama can show some growth year unlike other ports which can show contraction in bunker sales volumes. Secondly, according to Ship and Bunker, maritime news intelligence have given a full forecast for 2017 saying that “One of the Best Oil Years” crude being capped at $60 (Ship and Bunker , 2016) so this could give a positive indication for the bunker prices to rise further.

1.6 **Problem Statement**

This paper builds upon the contribution of (Stefanakos and Schinas, 2014) and (Chevallier and Ielpo, 2014) researches and investigates changes in volatility in the bunker market using modeling techniques like E-GARCH in time series data of IFO 380cSt IFO 180cSt Singapore bunker prices. The results obtained have analysis of the positive and negative leverage effects seen in the two Bunker specifications. Also the research extends its investigation the effect of bunker prices by understanding the level of significance of one IFO 380 bunker specification over 180 bunker specifications and vice versa using Bivariate Analysis.

1.7 **Motivation to do the Research**

The research has given three main motivations and because of which the research is performed. Firstly the study would help traders and the risk managers to forecast the Bunker prices. Secondly it will give an idea about the positive and negative shocks in the Bunker Markets. Thirdly, the research can help the risk managers to take correct risk management (Hedging) strategies should be chosen to mitigate the losses in the maritime industry.

Chapter 2
Review of Literature

2.1 **Studying Volatility in Energy Prices**

In studies related to volatility the bunker prices, researches like (Stefanakos and Schinas, 2014) have stated that this study was important for operators as the bunker prices affect the economic and financial planning. It has used in studying the volatility of marine fuel prices and have used bivariate non-stationary model. It is seen that the methodology forecasts of a tetra-variate and an octavariate time series of bunker prices are produced are in agreement with actual values.

On similar terms studies done (Pedrielli, Lee and Ng, 2015)had proposed a game theory to examine and optimize the parameters of a Bunkering contract especially the fuel price fluctuations. It was found out that under given conditions the supplier and the buyer establish the bunker quantity and maximizes the profit and minimize the refueling cost.

The study (Alizadeh, Kavussanos and Menachof, 2004) however was based on the effective hedging against marine fluctuations at the major ports like Rotterdam, Singapore and Houston. Examinations were done using the crude oil and petroleum future contracts traded at NYMEX and IPE. The research has used dynamic hedge ratios and out-of-the sampling hedging. Differences occurred mainly because of the hedging effectiveness across regional markets attributed to the varying regional supply and demand factors in each market. It was found that the most effective futures instruments for sample hedging of spot bunker prices in Rotterdam and Singapore are the IPE crude oil futures, while for Houston it is the gas oil futures.

Table—1

Literature studies on Volatility in Energy Prices with the Research Gap.

S. no	Title of the Paper	Author	Journal Name	Research Gap
1)	Forecasting bunker prices; A non-stationary, bivariate methodology	Ch.N. Stefanakos and O. Schinasb	Transportation Research Part C: Emerging Technologies	A similar methodology can be applied to study the relationship between IFO 380 and180.
2)	Optimal bunkering contract in a buyer–seller supply chain under price and consumption uncertainty	Giulia Pedrielli, SzuHuiNgb, Loo Hay Leeb	Transportation Research Part E: Logistics and Transportation Review	No E-GARCH modeling done.
3)	Hedging against bunker price fluctuations using petroleum futures contracts: constant versus time-varying hedge ratios	Amir H. Alizadeh, Manolis G. Kavussanos& David A.Menachof	Applied Economics	Bunker Price GARCH modeling was not done.

2.2 GARCH Models in Energy Sector

Several studies have used GARCH models in crude oil benchmarks (WTI and Brent) like (Chang, McAleer and Tansuchat, 2011), (Byun and Cho, 2013), (Kristjanpoller and Minutolo, 2016) and (Hou and Suardi, 2012). (Chang, McAleer and Tansuchat, 2011) the study used models like DCC, VARMA- GARCH, BEKK and diagonal BEKK are used for crude oil spot and futures returns of two major benchmark international crude oil markets, Brent and WTI. The results had shown that the optimal portfolio weights of all Bivariate volatility models for Brent suggest holding futures in larger proportions than spot. For WTI, DCC, BEKK and diagonal BEKK suggested the holding crude oil futures till spot, but DCC and VARMA-GARCH suggested holding crude oil spot to futures.
The study (Kristjanpoller and Minutolo, 2016) is a hybrid model is analyzed to predict oil price return volatility. Likewise in the study (Hou and Suardi, 2012) had used of parametric GARCH models to characterize crude oil price volatility is widely observed in the literature and forecast oil price return volatility. The study has focused on two crude oil markets, Brent and West Texas Intermediate (WTI) and the out-of-sample volatility forecast of the nonparametric GARCH model yields superior performance in comparison to parametric GARCH models. The results for forecasting of oil price are accurate based on nonparametric GARCH model.
In (Lv and Shan, 2013) modeling on natural gas market volatility using GARCH-class models with a long memory and fat-tail distributions. The study did the forecasting of price volatilities of spot and futures prices. Secondly, forecasting volatility was defined on the basis as the price differential between spot and futures. The evidence showed that nonlinear GARCH-class models with asymmetric effects have the greatest forecasting.

The research (Suk JoonByun, 2013) examines the volatility abilities of three approaches: GARCH-type model that uses carbon futures prices, an implied volatility from carbon options prices, and the k-nearest neighbour model. It was concluded that GARCH-type models perform better than an implied volatility and the k-nearest neighbour model. This means that carbon options have little information about carbon futures due to their low trading volume. The volatilities of energy markets are also studied, i.e., Brent oil, coal, natural gas, and electricity, forecast following day's carbon futures volatility. Results have shown that Brent oil, coal, and electricity may be used to forecast the volatility of carbon futures. Another advanced study (Segnon, Lux and Gupta, 2017) used models for carbon price volatility and used multi fractal models. The study provided a comparative application of these models to carbon dioxide emission and allowance prices from the European Union Emission Trading Scheme and evaluated their performance with up-to-date model comparison tests based on out-of-sample forecasts of future volatility and value-at-risk.

In (Raju, 2016) analysis volatility of New Ship Building prices of LNG carriers was done. GARCH and EGARCH methods were applied. The results showed that there is a great deal of volatility in the new ship building prices of LNG vessels. It was also identified that negative shocks were more persistent the positive shocks.

The study (Charfeddine, 2016) used Fractional GARCH-class of models, Energy futures time series. It is being used in the crude oil, heating oil, RBOB regular gasoline and the propane futures energy with the one, two, three and four months. The result in the volatility is confirmed by the superiority of the FIGARCH and FIEGARCH models compared with the Markov switching GARCH models in terms of out-of-sample forecasting models.

Many models like the AR(1)-GARCH(1,1) to the AR(1)-GARCH(1,1)-X, AR(1)-GARCH(1,1)-M-X and the bivariate AR(1)-GARCH(1,1)-M-X were used in the study (Carroll, 2012) where the research was one trading volumes on firm-level data for the 20 largest Fortune 500 stocks. The main findings, the trading volumes are significant and positively signed in the volatility of returns equations for most firms, acting to reduce the persistence and to eliminate the need for GARCH terms.

Other disciplines like in researches done by (Girish, 2016) had also included the Spot electricity, ARMA-GARCH models, Time series & Price forecasting of electricity. Studies of (Jeon and Taylor, 2016) uses wave energy flux was done by GARCH and including unconditional and conditional kernel density estimation, uni-variate and bivariate autoregressive moving average generalized autoregressive conditional heteroskedasticity (ARMA-GARCH) models, and a regression-based method. (Chiou-Wei et al., 2016) studied the relationship analysis between energy consumption and economic growth for five Asia-Pacific countries. Model like bivariate exponential GARCH (EGARCH-M) were used in the mean model in which we incorporate economic uncertainty, real oil price and real exchange rate in addition to energy consumption and real GDP. While researchers like (Vortelinos, 2015) HAR (Heterogeneous Auto-Regressive Model); Principal Components Combining; Neural networks; GARCH; Volatility studies are used in the study. GARCH models were used to test the efficiency of the markets (Narayan, Liu and Westerlund, 2016).

Table -2

Literature studies on GARCH models in Energy Prices with the Research Gap.

S.no	Title of the Paper	Author	Journal Name	Research Gap
1)	Crude oil hedging strategies using dynamic Bivariate GARCH	Chia-Lin Chang, Michael McAleer , RoengchaiTansuchatf	Energy Economics	No E-GARCH used for the Bunker price data.
2)	Study of Volatility of New Ship Building Prices in LNG Shipping	T. BangarRaju , Vikas S. Sengar , R. Jayraj , N. Kulshrestha	International Journal of e-Navigation and Maritime Economy	LNG prices are taken into account and no Bunker prices are analyzed.
3)	Modeling and forecasting the volatility of carbon dioxide emission allowance prices: A review and comparison of modern volatility models.	MawuliSegnona, Thomas Luxb, RanganGuptad	Renewable and Sustainable Energy Reviews	Volatility are analyzed for the Carbon dioxide emissions and No empirical GARCH analysis used on Bunker prices.
4)	Breaks or long range dependence in the energy futures volatility: Out-of-sample forecasting and VaR analysis	CharfeddineLanouar	Economic Modelling	No volatility analyzed between the Bunker Specifications.
5)	Do trading volumes explain the persistence of GARCH effects?	Rachael Carroll &Colm Kearney	Applied Financial Economics	Involves Trading volumes and no mention of Bunker analysis using GARCH.

6)	Spot electricity price forecasting in Indian electricity market using autoregressive-GARCH models	G.P. Girish	Energy Strategy Reviews	Bunker prices volatility analysis was not done.
7)	Short-term density forecasting of wave energy using ARMA-GARCH models and kernel density estimation	JooyoungJeon, James W. Taylor	International Journal of Forecasting	No volatility check for Bunker prices. The study mentions about wave energy.
8)	Controlling for relevant variables: Energy consumption and economic growth nexus revisited in an EGARCH-M (Exponential GARCH-in-Mean) model	Song-ZanChiou-Wei, Zhen Zhu, Sheng-Hung Chen, Sheng-Pin Hsueh	Energy, 2016	No relationship testing between Bunker grades.
9)	Forecasting Realized Volatility: HAR against Principal Components Combining, Neural Networks and GARCH	Dimitrios I. Vortelinos	Research in International Business and Finance, 2015	No Bunker prices analysis done.
10)	Time series forecasting with the WARIMAX GARCH method	J.M. Corrêa, A.C. Neto, L.A. Teixeira Júnior,E.M.C. Franco, A.E. FariaJr	Neurocomputing 2016	Simple GARCH is used for time series analysis. No mention about Bunker.
11)	Forecasting volatility of oil price using an Artificial Neural Network-GARCH model.	Werner Kristjanpoller, Marcel C. Minutolo	Expert Systems With Applications 2016	Volatility testing for Oil is done but No volatility check for Bunker prices.

12)	Estimation and inference in univariate and Bivariate log-GARCH-X models when the conditional density is unknown	GenaroSucarrata, Steffen Grønneberga, Alvaro Escribano	Computational Statistics and Data Analysis 2015	Univariate and Bivariate modeling done but no mention on Bunker.
13)	Forecasting carbon futures volatility using GARCH models with energy volatilities	Suk JoonByun, Hangjun Cho	Energy Economics 2013	No empirical research on Bunker Volatility.
14)	Modeling natural gas market volatility using GARCH with different distributions	XiaodongLva,c,∗, Xian Shanb	Physica A 2013	No mention for Bunker price volatility.
15)	A nonparametric GARCH model of crude oil price return volatility	AijunHou a, Sandy Suardi	Energy Economics 2011	Bunker Price GARCH modeling was not done.
16)	A GARCH Model for Testing Market Efficiency	Paresh Kumar Narayan Ruipeng Liu Joakim Westerlund	Int. Fin. Markets, Inst. and Money	Bunker Price GARCH modeling was not done.
17)	Energy markets volatility modeling using GARCH	Olga Efimova, ApostolosSerletis	Energy Economics 2014	Bunker Price GARCH modeling was not done.

Studying through the different articles the Literature Gap is quite evident (mentioned below) to study volatility and leverage effect.

2.3 **Literature Gap**

The following are the three gaps indentified:

GAP1. In the following papers it is observed that studies on energy prices and volatility are done. Different GARCH, BEKK, DCC, Bivariate VARMA are used in varied energy forms like crude oil, natural gas along with their price indexes, carbon, electricity markets and researches pertaining to the financial world were also studied. The studies were limited in the bunker markets.

GAP2. It was that, E-GARCH modeling were confined to studies like modeling for future prices of crude in NYMEX and volatility study between oil and gas inventory. It was used in studies to estimate static and dynamic long run and short run volatility and leverage effect. There were limited numbers of studies in the shipping industry involving E-GARCH modeling.

GAP3. Moreover, uni-variate and multivariate studies are done on majorly to measure some kind of effect and causal relationship of one variable over another. In commodities like Oil and Natural Gas Electricity prices, to calculate value at risk for Brent Crude Oil and Natural Gas and to study an impact of economic activity with crude price uncertainty. Hence, limited number of studies was done on bunker markets using Bivariate analysis.

To summarize modeling tools like E-GARCH for volatility analysis in bunker prices is one of the simplest modeling technique which also explains the leverage effect which the other GARCH models like GARCH (1.1) and simple GARCH, ARCH model fails to include. So this research involves Bivariate analysis and use to models like E-GARCH to understand the bunker prices specifically using bunker grades IFO 380 cSt and 180 cSt.

Chapter 3

Research Methodology

Research is the most important and basic part of any business with deep investigation, where the facts and features of any branch as well as industry can be understood. Research is the systematic effort to gain new knowledge. Empirical research will be applied in this study. It involves direct and indirect observation or experience or empirical evidence which can be analyzed quantitatively or qualitatively. Through quantifying the evidence some analysis can be drawn out based on the research objectives.

3.1**Research Design: Empirical Research**

This design involves use of past demand and the objective is to identify the pattern in the historic data and forecast this for future. The forecasting of the bunker prices is performed using 15 years historic bunker prices for IFO 380 and 180 cSt Singapore prices.

3.2 **Data Collection**

- Sample is Bunker prices at Singapore for IFO 380 cSt and 180 cSt Bunker specifications from January 2000 to October 2016 [15 years].
- Analysis of secondary data of fundamental variables are quantitative in nature

3.3 **Sample Size**

- Monthly data for 380 cSt and 180 cSt Singapore bunker prices are used in the study from January 2000 to October 2015.
- Total sample size 190 observations (15 years monthly data)

3.4 **Sources of Data**

This study only uses Secondary Data
- Sources of Secondary data are
1) IFO bunker prices for 380 and 180 cSt are obtained from the Drewry Maritime Services and Bunker database, Bunker newsletter by experts.
2) Journals, Bunker World websites, Platts price lists.

3.5 **Analysis of Data**

- Analysis is carried out using E-view (student version lite 9.5) and Mendeley software. All tests performed and results obtained in the Analysis chapter are from E-views.

3.6 **Tools and Models**

3.6.1**Basic Unit Root Theory** is to test whether a time series variable is non-stationary and possesses a unit root.

Augmented Dickey–Fuller (ADF) is a most popular type of Unit root test. According to (Said E. Said and Dickey A.David, 1984) this test requires hypothesis testing; where null hypothesis is when unit root is present in a time series sample while, the alternate hypothesis fails to show the series being stationary.

3.6.2**Exponential Generalized Autoregressive Conditional Heteroskedasticity- (E- GARCH)**

The simple GARCH model analyses volatility but is unable to capture the leverage effect. It only has the magnitudes of the historical data but is unable to tell whether the effect is positive or negative. This symmetric of the effect describing the negative shocks is observed to be higher in volatility than the positive shocks is explained under E-GARCH model hence is considered better than simple GARCH (Nelson, 1991).

For interpretations of data, left side is a log term is an indication to show leverage effect is exponential in nature and $\boldsymbol{\gamma_i}$< 0. This $\boldsymbol{\gamma_i}$is the magnitude of the persistence is variance in the data. $\boldsymbol{\alpha}$ **and** $\boldsymbol{\beta}$ shows the positive and negative leverage effects. If $\boldsymbol{\beta = 0}$ it means there is asymmetric volatility. If $\boldsymbol{\beta > 0}$ and significant it means the volatility is asymmetric and positive in nature. Otherwise $\boldsymbol{\beta < 0}$ and significant it has asymmetric volatility but negative in nature. And if $\boldsymbol{\beta = \text{negative}}$ it means leverage effect is present.

The equation for the E-GARCH modeling is given by (Nelson, 1991)

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{q} \left(\alpha_i \eta_{t-i} + \gamma\left(\left|\eta_{t-i}\right| - E\left|\eta_{t-i}\right|\right)\right) + \sum_{i=1}^{q} \log \sigma_{t-j}^2)$$

$$\text{and } \epsilon_t = \sigma_t \eta_t \qquad \text{Equation3.1}$$

3.6.3**Bivariate Analysis**

The Bivariate Equation explains the causal relationship between 2 variables.

$Y_i = \beta_0 + \beta_1 (X) + \varepsilon$explains; Equation 3.2

Y_i= Estimated or Predicted Value

$\beta_{0} =$ Intercept Value

β1 (X) = Slope of the Equation

ε = Error term

3.6.4**LM Tests –**

In the study (Baltagi and Li, 1991) mentions that LM Tests are carried for spatial and serial correlation. These are developed by Breusch and Pagan (1979, 1980). One can test for serial correlation, assuming there are no random effects, using the LM test derived in (Godfrey 1978), (Breusch and Pagan, 1980). The econometrics book by (Gujarati, 2004), defines Serial Correlation as a relationship between a given variable and itself over cumulative time intervals.

3.6.5**Heteroskedasticity Tests-**

The study (AndreeaHalungaa, 2017) mentions about heteroskedaticity and Breusch-Pagan test. Econometrics book by (Gujarati, 2004) have defined heteroskedasticity is a condition when the standard deviation of a variable is monitored over a period of time is non-constant. This arises in two forms conditional heteroskedasticity identifies non-constant volatility when the future periods are high and low volatility cannot be identified. Unconditioned heteroskedasticity is when futures period is high and low volatility can be identified.

3.7 **Research Objectives**

<u>Objective 1-</u>

To study the volatility of bunker prices of 380cSt and 180cSt from January 2000 to October 2015 using E- GARCH.

<u>Objective 2</u>-

To investigate the effect of bunker prices by understanding the level of significance of one IFO 380 bunker specification over 180 bunker specification and vice versa.

3.8 **Scope of Study**

The study is confined to the IFO 380cSt and IFO 180cSt bunker grade specifications and it involves 15 years of financial years. The study has considered one of major bunkering hub viz, Singapore. The objectives of the study are achieved by using E- GARCH modeling techniques for volatility and Bivariate Analysis.

3.9 **Limitations of the Study**

-Study did not involve all the bunker specifications present.
-The study did not involve all the bunkering hubs like Fujairah, Rotterdam and Houston.
- Study did not use other form of volatility analysis like the average approach drift methods etc. and did not include all the GARCH and ARCH models.
- Many reasons impact bunker prices apart from other bunker grade prices.

Chapter4

Data Analysis and Interpretations

The following chapter exhibits and discusses the results for the Bunker 180cSt and 380cSt specifications. These results are in accordance to the research objectives that the study tends to answer.

4.1**Descriptive Analysis**

Descriptive Analysis describes the basic features of the data in a study. They provide a brief about the sample collected along with simple graphics analysis. It also includes the basic statistical analysis of the data for example mean, median, mode, standard deviation, skewnness etc.

4.1.1**IFO 380 cSt Bunker**

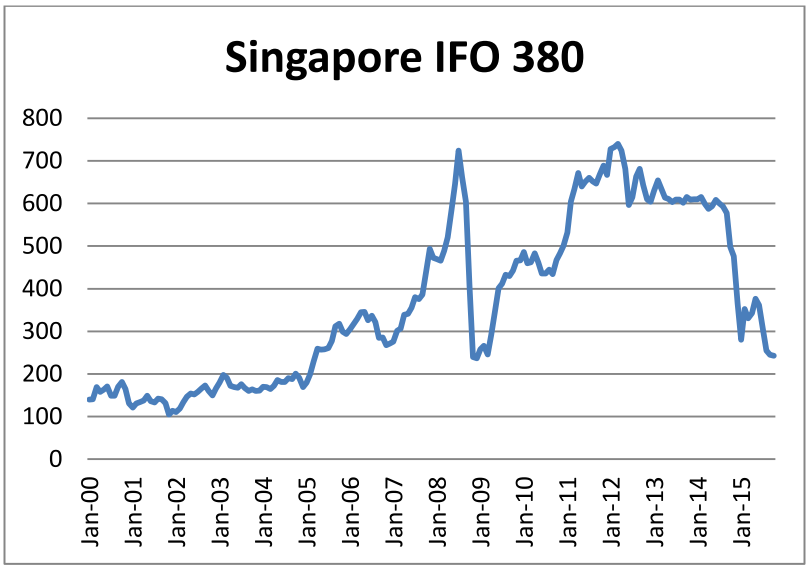

Figure-2 Volatility shown in Bunker Prices of IFO 380

(from Jan 2000 to October 2015)

This graph shows the fluctuations in the bunker prices for the Singapore IFO – 380 ($/tonne) on the Y axis. The data available was from year 2000 (January) to 2015 (October) ie (190 observations) on the X axis. The graph represents fluctuations and shows 2008 as the highest point in the data set and going to one of the lowest points in 2009. These prices are well correlated with the crude price movements.

4.1.2 **IFO 180 cSt Bunker**

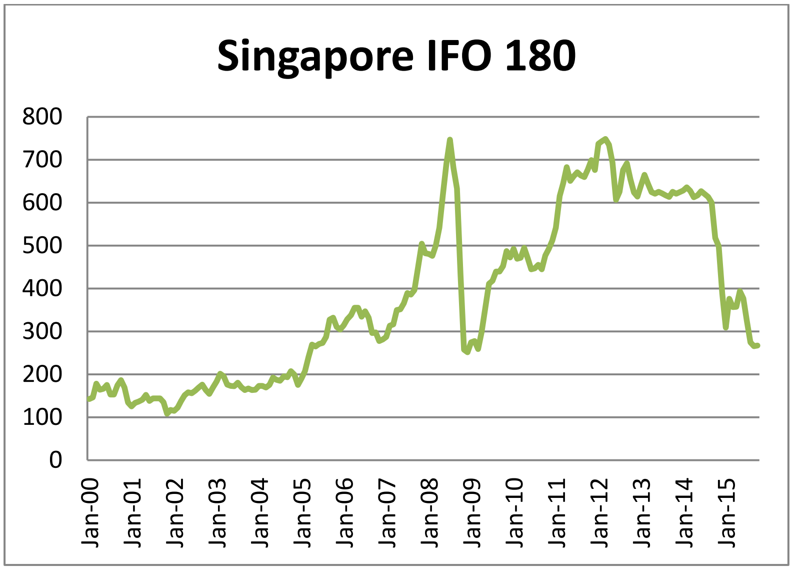

Figure 3 Volatility shown in Bunker Prices of IFO 380

(from Jan 2000 to October 2015)

This graph shows the fluctuations in the bunker prices for the Singapore IFO – 180 ($/tonne). The data available was from January 2000 to October 2015 (190 observations). The graph represents fluctuations showing its peak in 2008 going to its lowest points in 2009.

4.1.3 **Interpretations of the Descriptive Analysis**

The skewness is a measure of symmetry or the lack of symmetry while Kurtosis shows how the values are bundled in across the center of the distribution also known as a measure of data being heavy-tailed or light-tailed relative to the normal distribution. These both determine the shape of the distribution curve.

Parameters	Bunker Fuel 180	Bunker Fuel 380
Mean	377.93	367.50
Median	342.25	329.97
Maximum	748.38	739.63
Minimum	108.00	105.00
Std. Dev	195.50	191.78
Skewness	**0.32**	**0.34**
Kurtosis	**1.69**	**1.70**
Jarque-Bera	16.83	17.09
Probability	0.00	0.00
Sum	71807.50	69824.69
Sum Sq. Dev.	7223664.00	6951130.00
Observations	190.00	190.00

Table 3 Descriptive Analysis of IFO 180 and IFO 380

Interpretations

The skewness in the data for IFO 380 was observed as 0.340 which meant to have data distribution be approximately symmetric while Kurtosis is 1.697. Kurtosis less than 3 are said to be platykurtic showing high flatness and short tails in the data set.

Skewness observed in the data set for IFO 180 was observed as 0.340 which meant to have data distribution be approximately symmetric while Kurtosis is 1.697. Kurtosis less than 3 are said to be platykurtic showing high flatness and short tails in the data set.

4.2 **Unit Root Test- Augmented Dickey–Fuller test (ADF)**

In econometrics, an Augmented Dickey–Fuller test (ADF) tests the time series data to be stationary or not said by (Said E. Said and Dickey A.David, 1984)

4.2.1 **IFO380 cSt Bunker data**

ADF with 1 level Difference is performed and the following is the result output. We have chosen that the Null Hypothesis is Singapore IFO 380 has a unit root, which gives the probability of less that 0.05 (5%) hence the Null Hypothesis is accepted and shows that the series are stationary.

Null Hypthesis: D (Singapore IFO 380) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic – based on SIC max lag= 14)			
		t- statistics	Prob*
Augmented Dickey- Fuller test statistic		-8.589864	0.0000
Test Critical Test	1% level	-3.465202	
	5% level	-2.876759	
	10% level	-2.574962	

Table 4: ADF tests result output for IFO 380

4.2.2**IFO 180 cStBunker data**

ADF with 1 level Difference is performed and the following is the result output. The Null Hypothesis is Singapore IFO 180 has a unit root, which gives the probability of less that 0.05 (5%) hence the Null Hypothesis is accepted and shows that the series are stationary.

Null Hypthesis: D (Singapore IFO 180) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic – based on SIC max lag= 14)			
		t- statistics	Prob*
Augmented Dickey- Fuller test statistic		-8.578454	0.0000
Test Critical Test	1% level	-3.465202	
	5% level	-2.876759	
	10% level	-2.574962	

Table 5: ADF tests result output for IFO 180

4.3 **Exponential General Autoregressive Conditional Heteroskedasticity**

4.3.1 The following results are for IFO 380 cSt Bunker specifications

Dependent Variable is IFO 380 cSt

LOG(GARCH)= C(2) + C(3) *ABS(Resid(-1)/@SQRT(GARCH(-1)))+C (4)* RESID(1)/@SQRT(GARCH(-1))+C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	t-statistics	Prob
Mean Equation				
C	293.1495	4.718008	62.13417	$\boxed{0.0000}$
Variance Equation				
C(2)	-0.230310	1.277077	-0.180342	0.8569
C(3)	1.921725	0.845371	2.273232	$\boxed{0.0000}$
C(4)	0.137467	0.446811	0.307663	0.7583
C(5)	0.831768	0.153296	5.425892	$\boxed{0.0000}$

Table 6: E-GARCH tests result output for IFO 380

Interpretation

C is a constant and equation is known as the mean equation. It shows that the probability is 0.00 that means that the model is perfect fit and significant. The model shows C(2) is the constant of the variance equation, C(3) is the short-term shock or the ARCH equation, C(4) is for the leverage effect and C(5) is the long-term shock or the GARCH equation. Results for C(3) and C(5) are significant as the probability value is less that 0.05. Thus this means that, the model shows Short term shock persistence and Long term shocks persistence in the bunker prices of IFO_380 for the given 15 years.

4.3.2 **The following results are for IFO 180 cSt Bunker specifications**
Dependent Variable is IFO 180 cSt
LOG(GARCH)= C(2) + C(3) *ABS(Resid(-1)/@SQRT(GARCH(-1)))+C (4)* RESID(-1)/@SQRT(GARCH(-1))+C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	t-statistics	Prob
		Mean Equation		
C	169.1634	1.167977	144.8345	0.0000
		Variance Equation		
C(2)	-0.654897	0.854771	-0.766167	0.4436
C(3)	2.028486	0.470437	4.311920	0.0000
C(4)	0.485306	0.243085	1.996446	0.0459
C(5)	0.837919	0.129963	6.447383	0.0000

Table 7: E-GARCH tests result output for IFO 180

Interpretation

C is a constant and equation is known as the mean equation. It shows that the probability is 0.00 that means that the model is perfect fit and significant. The model shows C(2) is the constant of the variance equation, C(3) is the short-term shock or the ARCH equation, C(4) is for the leverage effect and C(5) is the long-term shock or the GARCH equation. Results for C(3), C(4) and C(5) are significant as the probability value is less that 0.05. Thus this means that, the model shows Short term shock persistence, Positive leverage effect which means the volume would be in the same magnitude in future and Long term shocks persistence in the bunker prices of IFO_180 for the given 15 years.

4.4Bivariate Analysis

Bivariate Analysis means the analysis of two variable data. In this case there are two time series data namely IFO 180 and IFO 380 Bunker data and it is used to find out if there is any causal relationship between two sets of values. In the research the analysis starts with the bivariate analysis and estimation of results are done using the raw data on default settings of E-views (without checking standardization in the given series) and it gave positive results**.** When the standardization was checked by taking log of the data series we got appropriate and positive results with interpretations analyzed below.

Result outputs for showing impact of one bunker specification price over other and vice-versa.

4.4.1 **Dependent Variable is DLOG(BunkerFuel180 cSt)** and Independent Variable is 380 cSt. Hence the impact of 380 cSt is measured over180 cSt is given below.

Variable	Coefficient	Std. Error	t-statistics	Prob
C	-0.000542	0.000804	0.674629	0.5007
DLOG(IFO380)	0.962790	0.008948	107.5980	0.0000
R-squared	0.983937		Mean dependent var	0.003341
Adjusted R-Squared	0.983851		S.D dependent var	0.087389
S.E of Regression	0.011105		Akaike info Criterion	-6.152277
Sum squared resid	0.023062		Schwarz Criterion	-6.117973
Log likelihood	583.3902		Hannan-Quinn criter	-6.138380
F-statistic	11454.82		Durbin-Watson stat	2.737493
Prob(F-statistic)	0.000000			

Table 8: Bivariate tests result using First difference (LOG) output for IFO 380

Interpretations:

Bunker Fuel 380 had a positive impact on Bunker fuel 180 at 1% level of significance. Also the adjusted R square is highly correlated ie it means that there are other factors affecting apart from price.

4.4.2**Dependent Variable is DLOG (Bunker Fuel IFO 380 cSt)** and Independent Variable is 180 cSt. Hence the impact of 180 cSt is measured over 380 cSt is given below.

Variable	Coefficient	Std. Error	t-statistics	Prob
C	-0.000508	0.000828	-0.612689	0.5408
DLOG(IFO180)	1.021964	0.009498	107.5980	0.0000
R-squared	0.983937		Mean dependent var	0.002907
Adjusted R-Squared	0.983851		S.D dependent var	0.090035
S.E of Regression	0.011441		Akaike info Criterion	-6.092631
Sum squared resid	0.024479		Schwarz Criterion	-6.058327
Log likelihood	577.7536		Hannan-Quinn criter	-6.078734
F-statistic	11454.82		Durbin-Watson stat	2.729613
Prob(F-statistic)	0.000000			

Table 8 Bivariate tests result using First difference (LOG) output for IFO 180

Interpretations:

Bunker Fuel 180 had a positive impact on Bunker fuel 380 at 1% level of significance. Also the adjusted R square is highly correlated ie it means that there are other factors affecting apart from price.

4.5 Breusch–Godfrey LM Test
The regression models to which the test can be applied include cases where lagged values of the dependent variables are used as independent variables in the model's representation for later observations.
For the LM test the following Hypothesis is made.
Ho (Null Hypothesis) = No Serial Correlation
and
H1 (Alternate Hypothesis) = Have a Serial Correlation

4.5.1 **LM Test for DLOG (Bunker Fuel IFO 380 cSt)**

Breusch- Godfrey LM test output for IFO 380

F- Statistics	7.695532	Prob F(6,181)	0.0000
Obs* R-squared	38.41445	Prob. Chi Square (6)	0.0000

Table 9 Results for Breusch- Godfrey LM test output for IFO 380

The result sheet below shows the LM is significant the Null Hypothesis is rejected, and thus the results are affected by serial correlation and because of this the results needs correction.

4.5.2 **LM Test for DLOG (Bunker Fuel IFO 180 cSt)**

Breusch- Godfrey LM test output for IFO 180

F- Statistics	7.039390	Prob F(6,181)	0.0000
Obs* R-squared	35.75882	Prob. Chi Square (6)	0.0000

Table 10 Results for Breusch- Godfrey LM test output for IFO 180

The result sheet below shows the LM is significant the Null Hypothesis is rejected, and thus the results are affected by serial correlationand because of this the results needs correction.

4.6Heteroskedasticity Tests

Heteroskedasticity as mentioned in the previous chapter, is a condition when the standard deviation of a variable is monitored over a period of time is not constant. Heteroskedasticity is when futures period is high and low volatility can be identified. Hence, heteroskedasticity test was tested below.

4.6.1 **DLOG(IFO 380 cSt Bunker Fuel)**

Heteroskedasticity Test: Breusch- Pagan- Godfrey

F- Statistics	0.621410	Prob F(1,187)	0.4315
Obs* R-squared	0.625975	Prob. Chi Square (1)	0.4288
Scaled explained SS	4.142155	Prob. Chi Square (1)	0.0418

Table 11 Hetroskedasticity test output for IFO 380

This result shows that there is no HeteroskedasticError present in the model has the Chi-Square value (1) is not coming significant.

4.6.2**DLOG(IFO 180 cSt Bunker Fuel)**

Heteroskedasticity Test: Breusch- Pagan- Godfrey

F- Statistics	1.018356	Prob F(1,187)	0.3142
Obs* R-squared	1.023673	Prob. Chi Square (1)	0.3116
Scaled explained SS	6.610802	Prob. Chi Square (1)	0.0101

Table 12 Heteroskedasticitytest output for IFO 180

This result shows that there is no HetroskedasticError present in the model has the Chi-Square value (1) is not coming significant.

4.7 Corrected LM tests

The LM Tests came significant, there was a requirement to correct the LM tests to solve the problem of Serial Correlation. The correction is done byNewey-Wes. The corrected results are as followed:

4.7.1**Dependent Variable is DLOG(BunkerFuel380)**

HAC Standard errors & co-variance (Bartlett kernel, Newey- West fixed bandwidth=5.0000
No. d.f adjustments for standard errors and co-variance

Variable	Coefficient	Std. Error	t-statistics	Prob.
C	-0.000508	0.000510	-0.995561	0.3207
DLOG (IFO180)	1.021964	0.011930	85.66000	0.0000
R-squared	0.983937		Mean dependent var	0.002907
Adjusted R-Squared	0.983851		S.D dependent var	0.090035
S.E of Regression	0.011441		Akaike info Criterion	-6.090035
Sum squared resid	0.024479		Schwarz Criterion	-6.058327
Log likelihood	577.7536		Hannan-Quinn criter	-6.078734
F-statistic	11454.82		Durbin-Watson stat	2.729613
Prob(F-statistic)	0.000000		Wald F- statistic	7337.635
Prob (Wald Fstatistics)	0.000000			

Table 13 Corrected LM test output for IFO 380

4.7.2**Dependent Variable is DLOG(BunkerFuel180)**

HAC Standard errors & co-variance (Bartlett kernel, Newey- West fixed bandwidth=5.0000

No. d.f adjustments for standard errors and co-variance

Variable	Coefficient	Std. Error	t-statistics	Prob.
C	0.000542	0.000502	1.080252	0.2814
DLOG (IFO380)	0.962790	0.010968	87.77791	0.0000
R-squared	0.983937		Mean dependent var	0.003341
Adjusted R-Squared	0.983851		S.D dependent var	0.087389
S.E of Regression	0.011105		Akaike info Criterion	-6.152277
Sum squared resid	0.023062		Schwarz Criterion	-6.117973
Log likelihood	583.3902		Hannan-Quinn criter	-6.138380
F-statistic	11454.82		Durbin-Watson stat	2.737493
Prob(F-statistic)	0.000000		Wald F- statistic	7704.962
Prob (Wald F statistics)	0.000000			

Table 14 Corrected LM test output for IFO 180

Chapter 5

Recommendations and Conclusions

The objective of the research included the study of volatility and leverage effects in bunker specifications namely IFO 180 and IFO 380 using E-GARCH. E-GARCH measures the short and long run shocks and also shows positive and negative leverage effects of the price returns. Secondly it investigates as to what impact does bunker grade IFO 180 has over IFO 380 and vice versa.

Major two observations were recorded as firstly, the bunker specification of IFO 380 cSt only showed short and long run shocks persistence (as the results analysis these two were significant at 5% level of significance) and no leverage effect was observed as value of C(4) in the output sheet is not significant (greater that 5%). Secondly, analyzing IFO 180 cSt had the similar results for short and long run shocks persistence (as the results analysis these two were significant at 5% level of significance) but had a positive leverage effect in C(4) value being significant at 5% level of significance. This positive leverage effects proved that it had the same magnitude of the volatility forecasted in future. It is recommended to the maritime industries that studying different energy derivatives (like the futures and options and collar strategies) in this case of volatility is important. However, there are short and long run shocks persistent in both the bunker specifications, thus hedging strategies is required for both.

In theory it is known, IFO 380 and 180 are indexed as per as crude oil as thus shows a positive relationship with each other. Thus once tested it was observed, that both IFO 380 and IFO 180 have a positive impact over each other at 1% level of significance but the results show that magnitude of volatility differs in both the bunker specifications. This means that when the prices of IFO 180 rises there is a rise in prices for IFO 380 and when the prices for IFO 180 falls then prices for IFO 380 falls but not with the same magnitude.

Finally results from the Bivariate analysis showed that there were no Heteroskedastic Errors found as the values were not significant but there was a problem of Serial Correlation (seen through LM tests) which were corrected eventually.